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Research paper

Compare the performance of different technologies of PV Modules using Artificial intelligence techniques

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ABSTRACT

In this paper, we applied the artificial intelligence technique (Support Vector Machine; SVM Classifier) to compare the performance of two different technologies of PV modules (class to class and backsheet to glass) after five (05) months of operation in Algeria under the same weather conditions (moderate and humid climate). We have a database for the outdoor monitoring of these two PV modules, consisting of data (I_{sc}, V_{oc}, P_{max}, I_{mp}, V_{mp}, T_m, T_{amb}, G, WD, WS, Date, Time) which are variables data, where the SVM creates the groups or class according to the conditions that we entered, after which it produces heatmaps that help us in reading the results and making the decision easily, unlike the classic methods which are very difficult. This method is applicable for comparison between several PV modules or several photovoltaic PV plants. It is enough just to give the database.

1. INTRODUCTION

Currently, photovoltaic solar energy is one of the most economical renewable sources. The constant increase in the prices of electrical energy combined with the optimization in the prices of the elements that integrate a photovoltaic park generates a direct increase in investment in these systems. For this reason, the average power in new generation installations is increasing day by day, with the need for systems capable of supervising and managing the installations in a permanent form and interacting with all the elements, thus ensuring efficiency. optimal, from both a technical and economic point of view. A photovoltaic installation in the MW range is equivalent to a large area of hectares to manage. Therefore, information and maintenance management is a complex task that makes it essential to have

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a monitoring tool that allows an agile and effective response to any incident that may occur. Photovoltaic (PV) monitoring systems are essential for evaluating and optimizing the performance of solar PV installations. They allow various data to be recorded and analyzed in real time to monitor the performance and efficiency of the system. This monitoring process helps evaluate energy production, exported energy, and self-consumed energy over different periods. Stakeholders use specialized software to monitor and analyze data, enabling them to make informed decisions regarding the operation and maintenance of PV systems. Photovoltaic energy monitoring systems can be divided into two broad categories: ground-based monitoring systems and space-based monitoring systems. Ground monitoring systems are the most widespread due to several advantages such as rapid and precise response; detection of energy losses and PV system failure and improvement of system performance. The main components used in ground systems are sensors that measure real-time variables of the monitoring system; a Signal conditioning unit for amplification and filtering; a Microcontroller for data transmission and a PC for analysis, display, and storage. Ground monitoring systems are essential to optimize the performance of photovoltaic installations. They make it possible to detect problems quickly and improve energy production. CIRCUTOR's SCADA solution for the supervision and management of photovoltaic parks makes it possible to obtain detailed information about the installation, in addition to real-time alarms, whether critical or not, for interaction with the system by ensuring and improving the performance of one or more installations in the same data acquisition system [1]. In recent years, photovoltaic energy technologies have witnessed rapid development by most countries by allocating financial subsidies for generating electrical energy using photovoltaic technology. Data analysis is essential for drawing research conclusions in the field of energy performance assessment of photovoltaic (PV) systems. However, this assessment is complicated due to the influence of many variables on the operation of a PV system. Among these variables, the ecosystem response is the main issue because it depends on factors such as solar radiation, cell temperature, ambient temperature, humidity, pollution, cloudiness, and airspeed. Different models have been used to evaluate the effects of these uncertainties [2]. Currently, standard benchmarks are used to evaluate the overall performance of a PV system, but they have shortcomings [3]. To improve the characteristics of available software, a two-step procedure was proposed, based on descriptive and differential statistics. This approach makes it possible to detect and locate malfunctions that would not be identified with standard benchmarks [4]. LabVIEW: is a graphical user interface that facilitates data acquisition and control of system parameters, particularly in the field of photovoltaic (PV) systems. Developed by a virtual instrument company, LabVIEW allows the collection, calculation, and analysis of operational and metrological data from PV systems. It also interacts with software such as MATLAB and provides designers with the ability to optimally control and manage PV systems. LabVIEW also allows capture noise to be removed using a high-pass filter, and it has been used to monitor and analyze the performance of PV systems, including calculating system efficiency and signal harmonic analysis. AC generated by the inverter, using techniques such as Fourier analysis. [5]. ANN learning is commonly used for time series forecasting and can be used to recognize the optimal behavior of a PV system. It is possible to design an NN-based environmental and operational parameter predictor with reasonable accuracy to detect undesirable situations that could result in a drop in energy production relative to the available solar radiation [6-8]. The artificial neural network is usually organized into layers, including an input layer that receives the data, an output layer that shows the response to the training data, and a hidden layer between the input and output layers. In this work we applied Machine learning to compare the performance of two different technology of PV modules (glass PV module and backsheet glass PV module) after five (05) months of operation in Algeria under the same weather conditions (moderate and humid climate), Table 1 Shows electrical characteristics of the two photovoltaic modules.

Table 1. Electrical characteristics of the two photovoltaic modules.

	PV 1	PV2
P_{max}	275W	260W
I_{sc}	9,38A	8,6A
V_{oc}	38,5V	38
I_{mp}	8,76A	8,1A
V_{mp}	31,4V	31V

In this work we will present 3 main steps, In the first step we will present the photovoltaic power plant, monitoring, and equipment, and in the second step we'll see the main theory of database analysis using artificial intelligence, SVM classifier, and heat map table. In the third step, we will present an example of analyzing databases of monitoring two different technologies of PV modules and a comparison between their performances using artificial intelligence.

2. MACHINE LEARNING

We use the term "artificial intelligence" or AI to designate computers and computer programs capable of performances usually associated with human intelligence. For example, the ability to interact with humans, to process large quantities of data, or to learn progressively and therefore to improve continuously. It is therefore a vast subject, in perpetual evolution!

In summary, if Artificial Intelligence is a very vast field that partly brings together algorithms that "do not make you dream", there are also more efficient algorithms, particularly in machine learning.

Appearing in the 1980s, machine learning (ML) is the application of statistical methods to algorithms to make them more intelligent. The challenge of ML is to construct curves that approximate the data and make it easy to generalize. It is therefore based on the ability of algorithms to receive a lot of data and to "learn" from it.

The support vector machine, which uses the optimization method, is studied during a series of coaching examples, for instance, called support vectors, which are characterized by the separation function. The machine can even calculate multiples related to these vectors. the choice function is calculated using support vectors and their multiples that the machine calculates for new examples [9].

SVMs seek to draw a boundary (called a hyperplane) that best separates different classes in your dataset. They perform well for high-dimensional data and are known for their accuracy, but the inner workings of the model can be more difficult to interpret. (we see in this paper) [10-13].

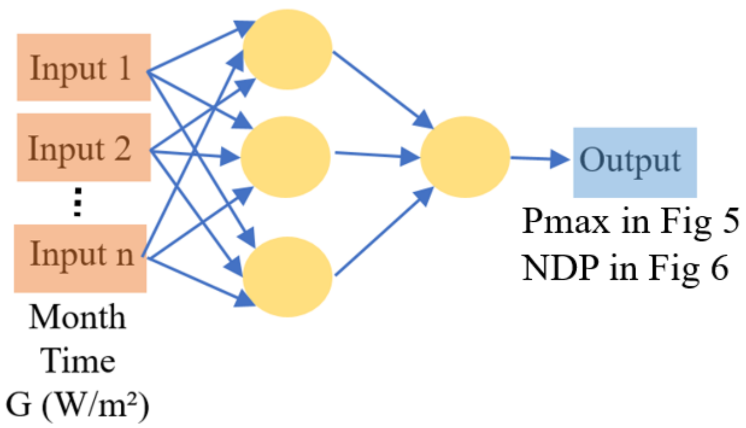

Figure 1. Architecture of SVM classifier (Neuron model)

2.1 Heatmap

Heatmaps are a useful visual aid for a viewer, allowing the rapid dissemination of statistical or data-based information. In contrast, heatmaps only provide selective information, thus obscuring the big picture of an issue; Heatmaps are also often prepared when only preliminary information is available [14]. Although heatmaps are used in various industries and circumstances, they are commonly used to show user participation on a website. Heatmaps came into vogue after the recession that started in 2008.

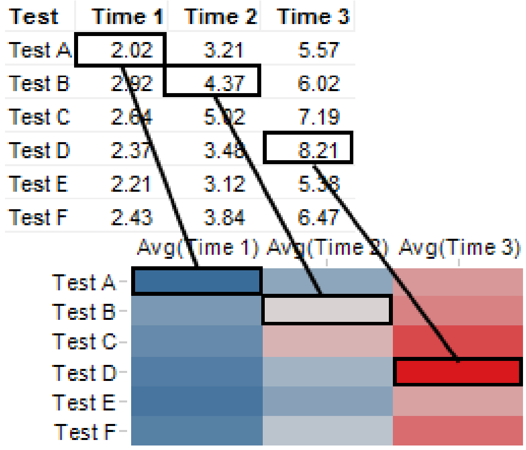

Figure 2. Color distribution in Heatmap

3. METHOD OF MEASUREMENT AND DATA PROCESSING

Data has been around since the dawn of human civilization; in recent years the internet and other digital technologies have made data more accessible than ever before enabling new opportunities for innovation. Data can take on many forms both digital and physical and have different formats like numbers, texts, audio, images, and videos that are related to a specific topic Many data are produced daily and to benefit from them they must be analyzed.

The measurement and collection of data is based mainly on several devices, including (Keysight 34972 A) see Figure 3. The database obtained consists of a group of sensors, namely (I_{sc}, V_{oc}, P_{max}, I_{mp}, V_{mp}, T_m, T_{amb}, G, WD, WS, Date, Time, and FF), to provide a huge amount of information and data for accurate analysis, and therefore the greater the amount of data, the more accurate the analysis.

This study was carried out in our laboratory, which is located in the annex of the Renewable Energy Development Center CDER, Ben Aknoun City, Algeria (Latitude 36◦44'44,94''N, Longitude 3◦00'46,80 E and Altitude 236 m).

Figure 3. Data acquisition (Keysight 34972A).

4. RESULTS AND DISCUSSION

In this paper, the application of ML is based on monitoring data of two (02) PV modules during 05 months with a step of measurement of 5 min, (this method is applicable for several PV modules see Fig 4, n: Number of PV modules).

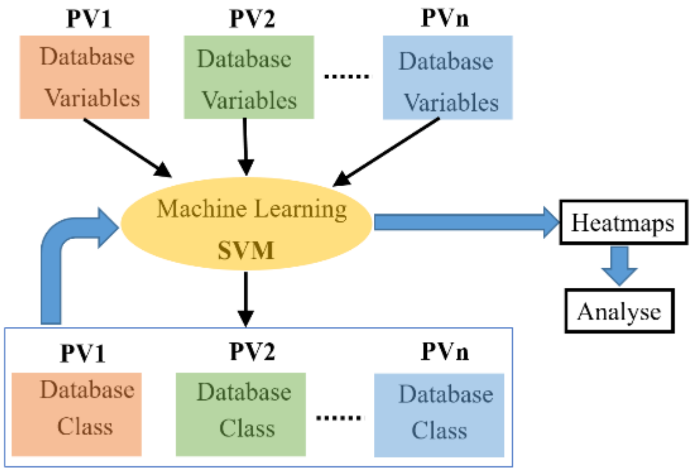

Figure 4. Diagram of method.

Figure 5. Represents Heatmap of time according to month and Pmax (W), color gradations, and their distributions represent numbers whether big or small. Here the darkest color represents the lowest values whenever the color is getting lighter the values increase. Power (Pmax) values (greater than 184W) are displayed in the time domain from 12h00-13h00 in February. The average values of Pmax below 146 W are displayed in the time domain from 11h00-12h00 and 14h00-15h00 in January and February. The weak and absence of power (black Zones) are recorded in the 06h00-09h00 and 17h00-20h00 where the number of data is zero 0 see Figure 6.

Dark green represents 0 values, when it lightens a little it gives us average values and when it becomes yellow, we reach the highest value (more than 900). We notice a high value of the number of data points (more than 900) is displayed when the irradiation (G(W)) is between 850-950 W/m² between 11h00-15h00. In which the average value (881) is displayed when the G(W) is between 950-1050 and the time is between 13h00-14h00.

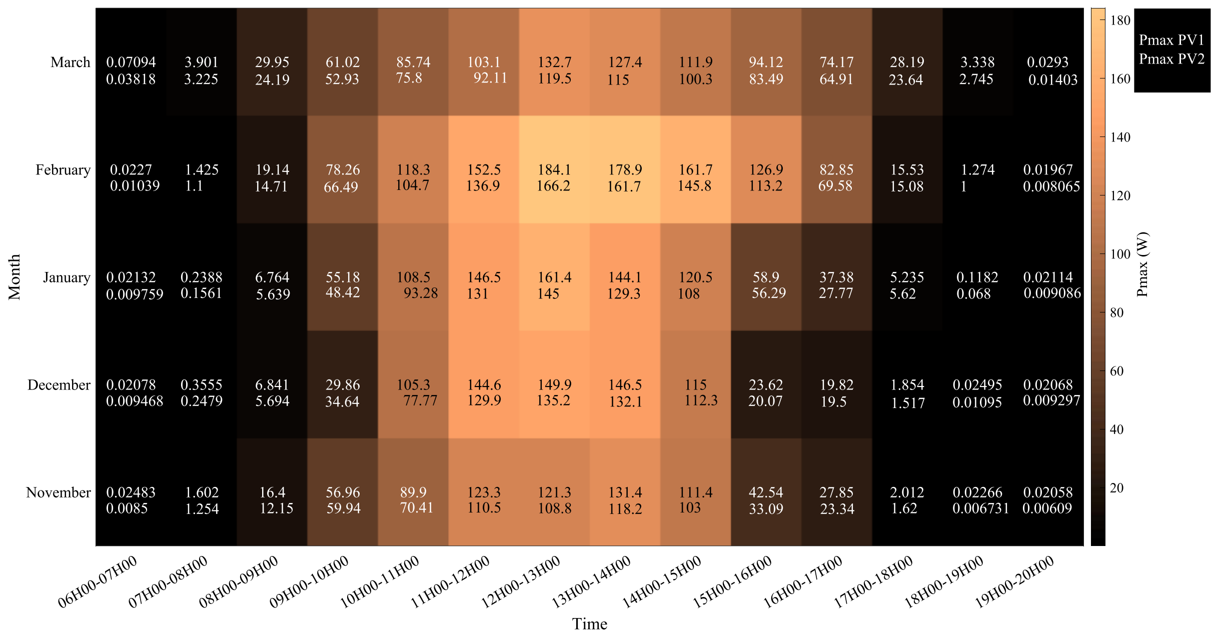

Figure 5. Maximum power supplied over a day in five (05) months

Figure 6. Represents Heatmap of Time according to G (W/m²) and number of data. Color gradations and their distributions represent numbers (digits) whether large or small. We note that the value of the number of data is large between 0-50 W/m², but does not affect photovoltaic, we the large value of the number of data displays 1640 when the users entered 18h00 -20h00.

This paper explored the application of heatmaps with SVM classification providing valuable insights and visual representation of data distribution allowing us to identify large datasets. However, it is important to note that the effectiveness of heatmaps and SVM classification depends on the quality and relevance of the data used. Our method is effective and fast in making decisions and facilitating the analysis process compared to some research in the field of monitoring data analysis, for example in Ref [15] the authors studied the analysis of 2000 PV modules in Korea by classical methods, but the work lacks the application of one of the artificial intelligence techniques due to the large amount of data that is difficult to analyze manually. Also included in the Ref [16] is the analysis of data of solar energy plant systems using a classic method. If the analysis were using artificial intelligence techniques, the results would be better.

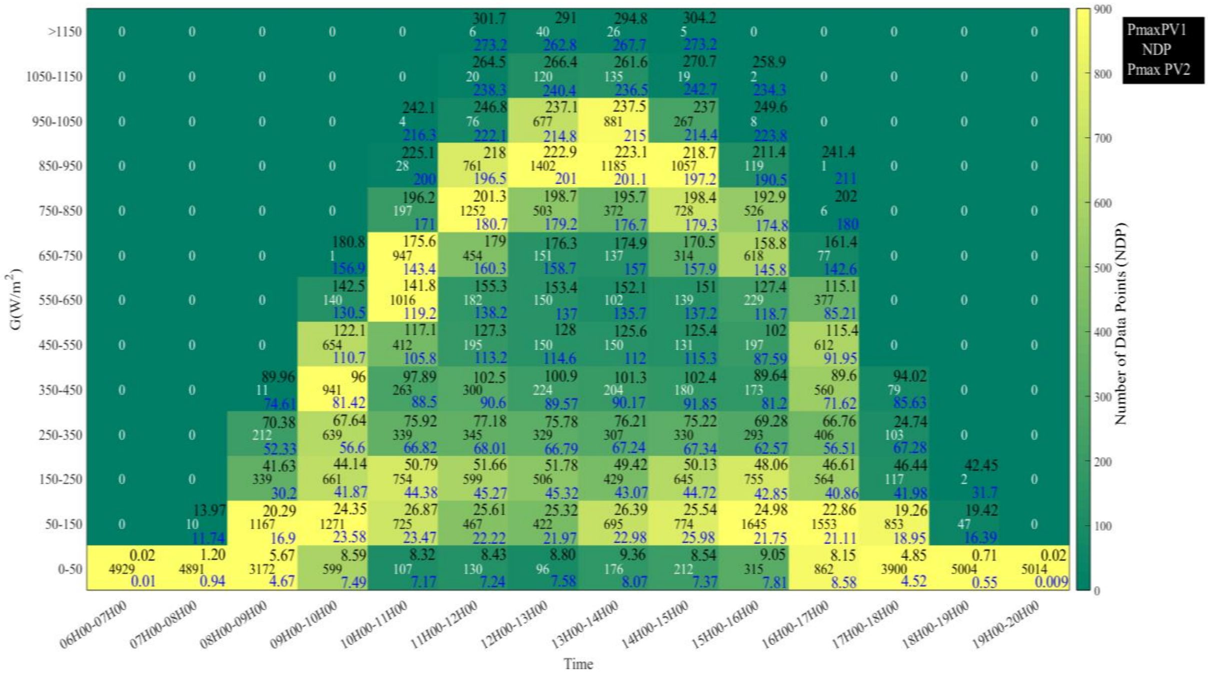

Figure 6. Number of Data points according to G (W/m^2) and Time in Five (05) months

5. Conclusion

This study shows the importance of ML and we spoke generally about AI, then we presented clearly and exhaustively the concept of machine learning introduced by Vladimir Vapnik, Support Vector Machines (SVM). We first provided an overview of SVMs and then delved into some fundamental mathematical aspects. At the heart of this classification method lies the search for an optimal hyperplane, capable of distinctly separating sets of data, and in the end, we presented the database of two different technologies of PV modules using Artificial intelligence techniques. This analysis has proven to be a highly effective and promising approach, through the utilization of advanced AI algorithms and machine learning models. By employing AI techniques, the monitoring of PV modules can gain a deeper understanding of their performances. The integration of heat maps with AI techniques enables real-time monitoring and analysis of key performance indicators, allowing the monitoring of PV modules to proactively respond to the performances or faults. Moreover, heat maps facilitate the identification of faults and correlations in the performance by mapping the flow. In this work, we tried as much as possible to collect and present information that analyzes the database and performance of two different technologies of PV modules using Artificial intelligence techniques, which is the backbone of the performance of PV systems. We tried to give all information about monitoring of PV systems including artificial intelligence and machine learning techniques such as SVM classifiers and heat map tables that make a revolution in the field of database. These new techniques have allowed us to extract valuable insights from vast amounts of data better than traditional methods we have known before.

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NOMENCLATURE

I_{sc}	Short-circuit current of PV module [A]	T_m	Temperature of PV module, measured at the backsheet [°C]
SVM	Support Vector Machine		
V_{OC}	Open-circuit voltage of PV module [V]	G	Measured in-plane irradiance [W/m^2]
P_{max}	Maximum power output of PV module [W]	WD	Wind direction
I_{mp}	PV module current at maximum power point	WS	Wind speed [m/s]
V_{mp}	PV module voltage at maximum power point [V]	Date	Date of measurement
T_{amb}	Ambient temperature [°C]	Time	Hour of measurement
NDP	Number of Data Points		

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